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Anomaly Detection of Turbopump Vibration in Space Shuttle Main Engine Using Statistics and Neural Networks

C. F. Lo*, K. Wu+ and B.A. Whitehead++

Abstract

The statistical and neural network methods have been applied to investigate the feasibility in detecting anomalies in turbopump vibration of SSME. The anomalies are detected based on the amplitude of peaks of fundamental and harmonic frequencies in the power spectral density. These data are reduced to the proper format from sensor data measured by strain gauges and accelerometers. Both methods are feasible to detect the vibration anomalies. The statistical method requires sufficient data points to establish a reasonable statistical distribution data bank. This method is applicable for on-line operation. The neural network method also needs to have enough data to train the neural networks. The testing procedure can be utilized at any time so long as the characteristics of components remain unchanged.

Introduction

The feasibility study for detecting anomalies in turbopump vibration data has been conducted with data from ground tests 902-473, 902-501, 902-519, and 904-097 of the Space Shuttle Main Engine (SSME). The study has been designed to analyze vibration data from each of the following SSME components: high-pressure oxidizer turbopump, high-pressure fuel turbopump, low-pressure fuel turbopump, and preburner boost pump as described in Ref. 1. The pre-processor module of the software system locates and classifies peaks in the power spectral density of each 0.4-sec window of steady-state data. Peaks which represent fundamental and harmonic frequencies of both shaft rotation and bearing cage rotation are identified by the module. Based on the statistics and neural network methods, anomalies are then detected by the amplitude of each of these peaks individually.

Using the statistical method, anomalies are detected on the basis of two thresholds set individually for the amplitude of each of these peaks: a prior threshold used during the first group of windows of data in a test, and a posterior threshold used thereafter. In most cases the anomalies detected by the statistics agree with those reported by NASA.

Using the neural networks, the amplitudes of each of these peaks are selected as input training data sets including normal and abnormal samples in a single test. The reserved testing data which have not been used to training the network in the same test are applied to assess the effectiveness and feasibility of the neural network approach. The HPFTP is the selected component for the current study. The rate of correct diagnosis to identify the normal or abnormal conditions is better than 95% of the total testing cases.

Current Systems

The prototype software systems have been designed for detecting anomalies in turbopump vibration data from ground tests of SSME by using the statistics and neural networks. They are described in the following sections after the sensor data pre-processor module.

Sensor Data Pre-processor

Vibration data was provided by NASA in the form of FFT from accelerometers mounted on the oxidizer and fuel pumps. A set of Fortran programs running on the UTSI VAX 11/780 has been developed to read these data tapes in NASA binary format which is inherently machine-dependent, to swap bytes from the NASA binary format to the VAX internal binary

* UTSI Professor, CSTAR Principal Investigator
+ CSTAR Research Engineer
++ UTSI Associate Professor

representation, and to convert the data into a portable ASCII format. After initial preprocessing on the VAX, the power spectra are stored in a form which can be quickly sent to any other platform at UTSI.

The **Frequence Extractor** is designed to identify the fundamental and harmonic frequencies of both shaft rotation and bearing cage rotation in each FFT window. First, peaks representing candidates for the shaft fundamental are reliably found based on an empirical linear fit, for each type of turbopump, of shaft rotation speed to SSME power level. The actual shaft and cage fundamental and their harmonics are then identified based on the ratio of cage to shaft rotation and the required consistency among the different harmonics of both shaft and cage. Freq-Extra is also designed to detect the intermittent frequencies whose amplitudes are above a specific value i.e. noise-level.

The typical data histogram of synchronous frequency plotted as the number density distribution from 1500 to 3900 units amplitude from 110 windows during the time period of 169 sec. to 213 sec. is shown in figure 1a. The typical data histogram of 240-hz from sensor 686 & 698 is shown in figure 1b. The data from sensor 613 shown in figure 2 are synchronous and sub-synchronous frequencies. All distribution is close to a "normal Gaussian" function. The 2nd, 3rd and 4th harmonics also have the similar distribution. Thus, the statistic mean and standard deviation of the data distribution are useful as the benchmark for the anomalies detection.

Statistical Approach

Two Versions of system. The earlier operational expert system is implemented on a Symbolics 3670 LISP machine (Ref 2). While good preliminary results have been obtained with this implementation, the LISP machine platform and the proprietary LISP language available on this platform both severely limit the portability of the expert system software. Also, the LISP language does not produce run-time code as efficiently as that produced by compilers of procedural languages.

In order to maximize the portability of the expert system software and improve the user interface, a re-implementation of its logic in the ANSI standard version of the C programming language has been accomplished on a PC (Ref 3). By employing ANSI standard C with the standard C I/O library and making few changes on machine-dependent portion, the software system can run on any platform which has sufficient memory and disk space for the operation of the software and for the data files it requires.
The statistic module is built in a **Anomaly Detector**. Anomalies are detected in a Anomaly Detector on the basis of thresholds (prior & posterior) and sequential criteria set individually for the amplitude of each fundamental and harmonic frequency of both the shaft and the cage. A prior threshold is used during the first few windows of data in a test, while data is first being accumulated for that test. Based on the accumulated data, a posterior threshold is then determined and used for the remainder of the test. Values for the prior threshold of 300% of the amplitude observed in the first window of data, and values for the posterior threshold of **5 standard deviations** above the running average of nominal data have been found to give good results for each of the ground tests analyzed to date. For the threshold criteria, anomaly of any identified frequencies is detected when its amplitudes is above its threshold. For sequential criteria, anomaly of any identified frequency is detected when anomalies keep showing in more than three consecutive windows.

The **User Interface** is graphics-oriented and mouse-driven. It provides users several windows to actively select as screen or hardcopy display, such as Process Status, Single FFT Window, Multiple FFT Windows, Waterfall plots , FFT Recall Windows and Output Files. With a mouse and simple pulldown menus, users can switch among these windows instantly anytime during processing. A sample of an interactive (or simulated on-line) session is given in Ref 3. The output files save detailed records for further examining of anomalies.

Results of Anomaly Detector. The results of anomalies detected by the system for the data from the ground tests 902-473, 902-501, 902-519 and 904-097 are summarized in Tables 1, 2, 3 and 4, respectively. Results obtained from NASA reports are also listed in a separate column for comparison. The exact time of detection of these anomalies by

NASA experts was not given in the documentation presently available from NASA, but will be pursued. The expert system results agree with those stated in the NASA reports, with two exceptions: (1) In test 902-519, HPFTP 50% Sub-synchronized frequency was not detected; and (2) In test 904-097: HPOTP second cage frequency was not detected by the system. These discrepancies require further investigation. The overall results assure us that the current strategy for detecting anomalies works reasonably well for most cases tested.

Neural Networks Diagnosis

For a specific turbopump component, the fundamental frequency and harmonics for the normal and abnormal conditions have their distinct characteristics as shown in Figures 3 and 4. The neural networks algorithm is a powerful pattern recognition method. Thus, the application of the neural nets techniques to the HPFTP's data from test 501 and 519 allows us to examine the feasibility in diagnosing the anomalies.

Neural Network Algorithm Description. A three-layer Back-Propagation (BP) Neural Network has been selected for the present study. Multilayer BP networks have been studied extensively and are widely used for pattern classification. Multilayer networks are able to classify non-linearly separable classes. In the present case, a three layer network is utilized including input layer, hidden layer and output layer. A 3-layered (input, hidden, output), fully connected, feed-forward network as shown in Figure 5. The normalized data sets are utilized. Both input and output are continuous-valued (between -0.5 and 0.5) vector. The outputs generated by the network are compared with the desired or target outputs. Errors are computed from the differences, and the weights are changed in response to these error signals as dictated by the Generalized Delta Rule (Ref 4). Thus, a BP network learns a mapping function by repeatedly presenting patterns from a training set and adjusting the weights. A commercial neural network program named ANSim (Ref. 5) is utilized for the training process as well as the testing process.

The Training Procedure is in the iterative fashion. It loops repeatedly over the set of training patterns until the total root mean square (RMS) error for all patterns is less than the specified value, e.g. 0.1. The Testing Procedure is forward feed processing.

Neural Network ANSim Software. SAIC ANSim 2.30 (Ref. 5) is a graphics oriented, menu-based artificial neural system (ANS) simulation program, which provides a complete complement of neural model development, allocation and analysis capabilities, including a powerful ANS creation, training, execution and monitoring tool. ANSim enables users to quickly implement and utilize ANS models using 13 paradigms such as Back Propagation (BP), Hopfiled Network, etc. ANSim enables the user to configure any number of ANS neural networks. It drives each network with a sequence of training and/or input data. For each model, ANSim will (1) monitor the response, (2) capture the output, and (3) save the configuration for later re-use. ANSim is integrated under Microsoft Windows to provide an effective, easy-to-use interface.

Floating Point Processor for ANSim. A PC 386 (VGA or EGA monitor) with the SAIC's Delta Floating Point Processor, which is a 22 MFlop AT bus compatible processor, allows for high speed Neural Network Systems training and processing.

Sample Data in the Form of Spectrum Plots. The typical data sets are obtained by the pre-processor module as shown in Fig. 3. consisting of synchronous frequency samples of normal and 240-hz abnormal data sets for sensor 696 and 698. The sensor 617 for Synchronous and Sub-synch frequency data is shown in Fig. 4. The reserved testing data shown in Figures 3 & 4, which have not been used for training the network in the same test, are applied to assess the effectiveness and feasibility of the network approach.

Results of Neural Networks. The component selected for the current study is the HPFTP. The HPFTP vibration data from ground tests 902-501 and 902-915, as shown in Figures 3 & 4, are utilized for the vibration anomalies detection study. The successful detection rate is higher than 95% to identify either normal or abnormal running conditions. The results have indicated that the application of Neural Networks to the available SSME vibration data sets in diagnosing existing faults in the data is a viable method.

Moreover, the actual clock time of computer computation on a PC-386 with Floating Point Processor are less than 1 minute for the training process. The testing time of the feed-forward process is near real time in the present case. It is important to know this computation time for planning on-line or off-line operations.

Future Plan. The satisfactory results given by the neural network approach can be reassured to investigate more cases and more fault scenarios. Since the ground testing data are limited, we decided to use the data generated from a NASA/MSFC numerical simulator for the follow-on study.

Summary

Automatic detection of anomalies in Space Shuttle Main Engine Turbopumps has been implemented as a prototype software system on a Symbolics 3670 LISP machine and on a PC. The system has demonstrated its capability in detecting anomalies in turbopump vibration data earlier than the indication provided by the redline detection mechanism. The present strategy based on the statistics distribution of data in detecting anomalies for SSME turbopumps seems to work well, even though some limited cases require further study. On the other hand, the limited application of neural networks to the HPFTP has also shown the effectiveness and feasibility to diagnose the anomalies of turbopump vibrations. The further application to data from a numerical simulator is warranted.

References

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Acknowledgements

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902-097	
NASA's REPORT	**PRESENT RESULTS**
LOX SIDE OBSERVATIONS * HPOTP: 2X CAGE PRESENT IN ACCEL DATA AT 104% & 109%RPL(0.4 Grms MAX.). CAGE RATIO CONSISTENT THROUGH TEST AT -0.434	2X cage does appear in Sensor 637 (PBP-RAD-45-1) and 638(PBP-RAD-45-3) around 160.0 sec., but system can not detect them now. *Analysis*: Maybe 5 std. is too high and these 2X cages don't show in more than 3 consecutive windows.
FUEL SIDE OBSERVATIONS * HPFTP: ANOM. FREQ. 1750-1800 HZ (10 Grms MAX). ANOM. FREQ. 560-600 HZ(7 Grms MAX)	Anom. Freq. 1750-1830 HZ presents in FASCOS-HPFP Sensors(696,697,698) around 97.0 sec..
* LPFTP: "330HZ" ACTIVITY ALONG WITH "330HZ" LPFTP SYNC. MODULATION SIDEBANDS. LPFP-RAD-240 ACCEL BAD (E/S +220 SEC.)	310HZ appears in Sensor 603(LPFT-RAD-180) at 393.4 sec..

TABLE 1

902-519	
NASA's REPORT	**PRESENT RESULTS**
LOX SIDE OBSERVATIONS * HPOTP: PASS ALL GREENRUN CRITERIA; ACCEPTABLE FOR FLIGHT.	NO ANOMALIES PRESENT IN PBP-RAD Sensors(637,638).
* LPOTP: ANOMALY PRESENT BETWEEN 800-900 HZ.	We don't have any LPOTP sensors.
FUEL SIDE OBSERVATIONS * HPFTP: 50% SUBSYNC. PRESENT @109% (MAX. AMP.-1.0Grams);POSSIBLY PRESENT @104%. FURTHER ANALYSIS NECESSARY.	System couldn't detect 50% subsync. *Analysis*: Lowering the 5 std. to 3 std. and dividing the white noise into two levels may help. Further work needs to be done.
* HPFTP: HPFT RAD 180 HAS LARGE SPIKE.	Sensor 612(HPFP-RAD-180) shows large spike at 1730HZ at 141.0 sec.. Sensor 617(HPFT-RAD-180) shows large spike at 5HZ at 91.4 sec...
* LPFTP: 330HZ PRESENT AT 104% & 109% MAX. AMP. 4.0 Grams FEEDS THRIUGH TO ALL TURBOPUMPS.	We don't have any LPFTP sensors.

TABLE 3

902-501	
NASA's REPORT	**PRESENT RESULTS**
LOX SIDE OBSERVATIONS * HPOTP: PASS ALL GREENRUN CRITERIA; NO ANOMALIES PRESENT.	No anomalies present in HPOP-WLD3 Sensors(705,706,707,708) and ES6740 sensors(520,522).
FUEL SIDE OBSERVATIONS * HPFTP: ANOM. FREQ.'s PRESENT AT 109% AT 240HZ and 950HZ(MAX.AMP.1.9 Grms and 1.5 Grms RESPECTIVELY).ANOMALIES ARE MODULATING ABOUT SYNC.. PASSES ALL GREEN RUN CRITERIA.	Sensor 697(FASCOS-HPFP) and Sensor 698(FASCOS-HPFP) present Anom. Freq.'s at 109% at 240HZ around 171.0sec., but no 950HZ shows ANOM. in FASCOS sensors (696,697,698).
* LPFTP: 330HZ APPEARS TO COALESCE WITH SYNC. CAUSING GREEN RUN SPEC. VIOLATION SYNC..	300HZ appears in Sensor 603(LPFT-RAD-180) at 91.4 sec..

TABLE 2

902-473	
NASA's REPORT	**PRESENT RESULTS**
LOX SIDE OBSERVATIONS * SYNCHRONOUS RUNNING ON HIGH SIDE AT 100% PWL 450 HZ	PBP sensors(635,636,637,638) show Anomalies of Synchronous (462.5HZ) around 360.0 sec..
FUEL SIDE OBSERVATIONS * PSEUDO 3N AT 1725 HZ COINCIDES WITH 3N AT S +70 SEC	We don't have any FUEL SIDE sensors.

TABLE 4

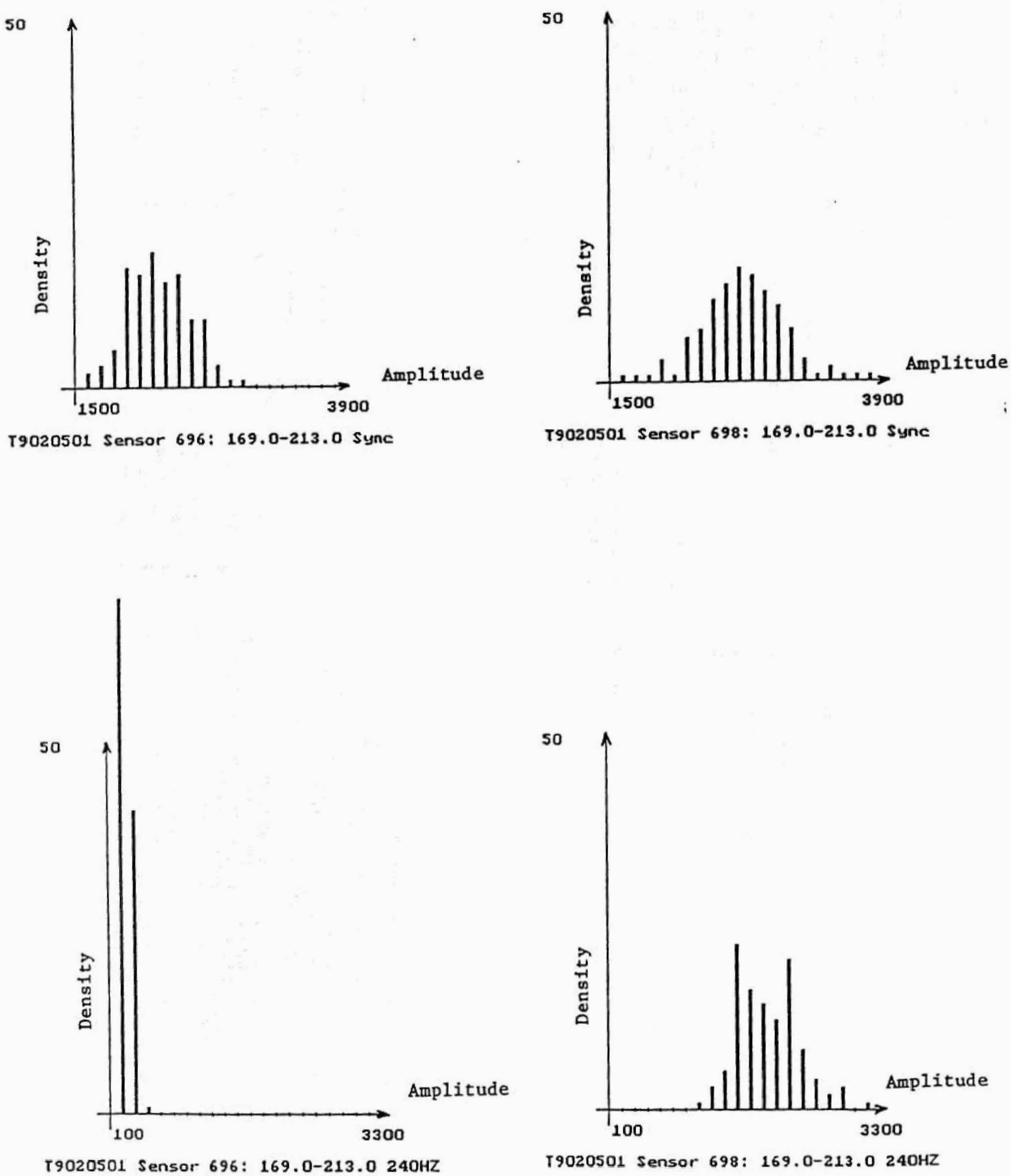

Figure 1. Data Histogram of Synchronous Frequency and 240-hz Frequency from Sensors 696 and 698.

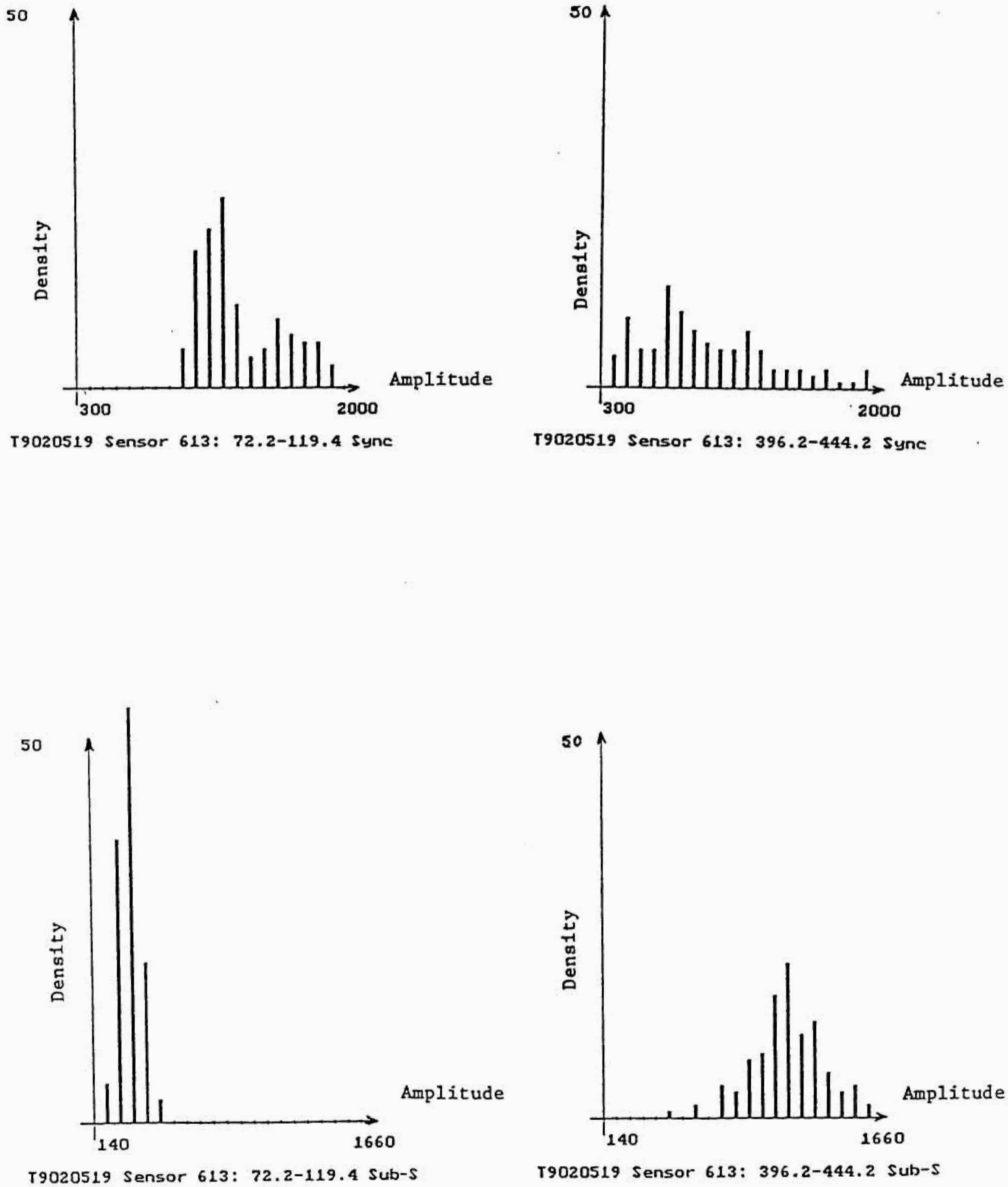

Figure 2. Data Histogram of Synchronous Frequency and Sub-synchronous Frequency from Sensor 613.

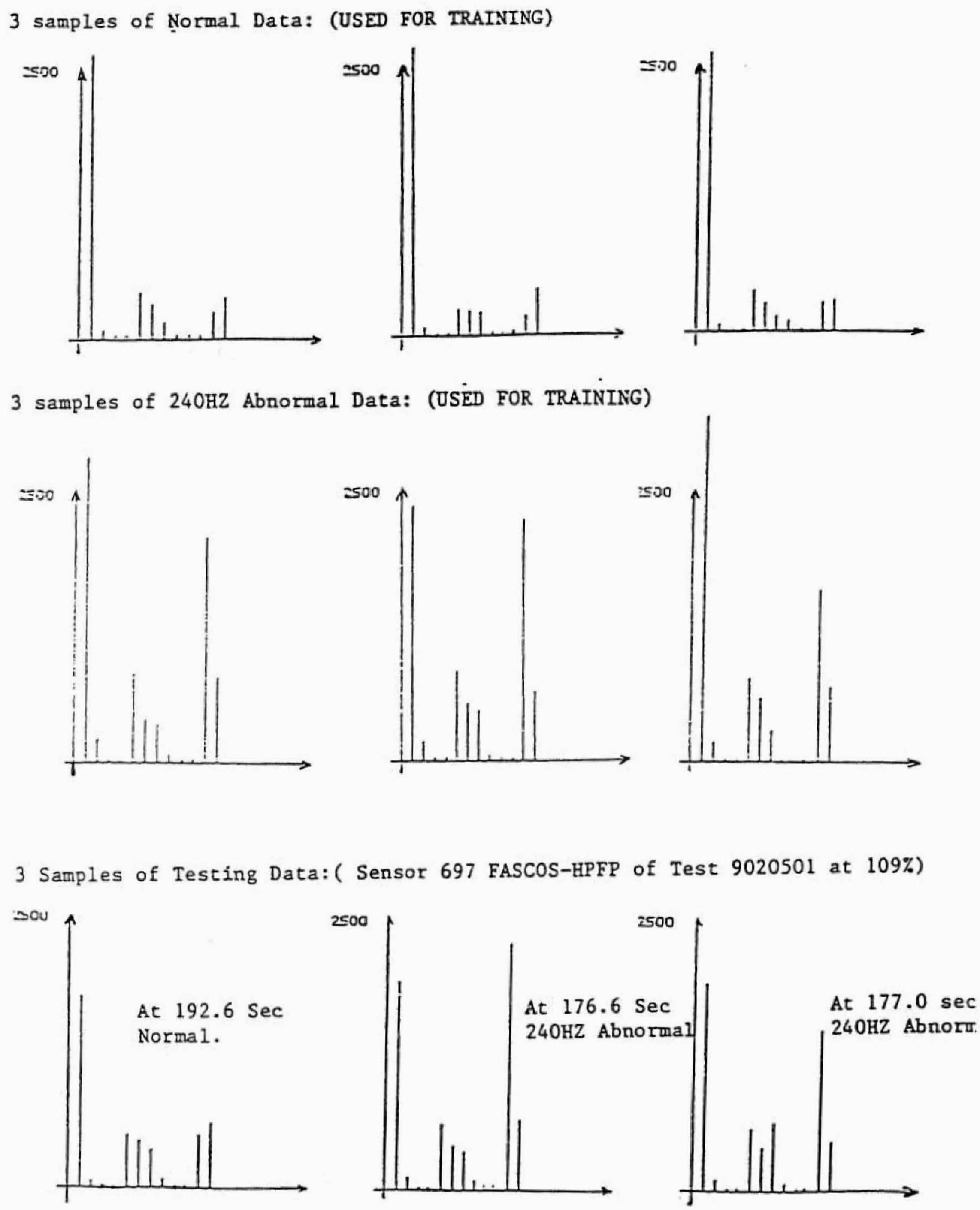

Figure 3. Samples of Normal and 240-hz Abnormal Data from HPFTP Sensors of Test 902-501 at the Thrust-level 109%.

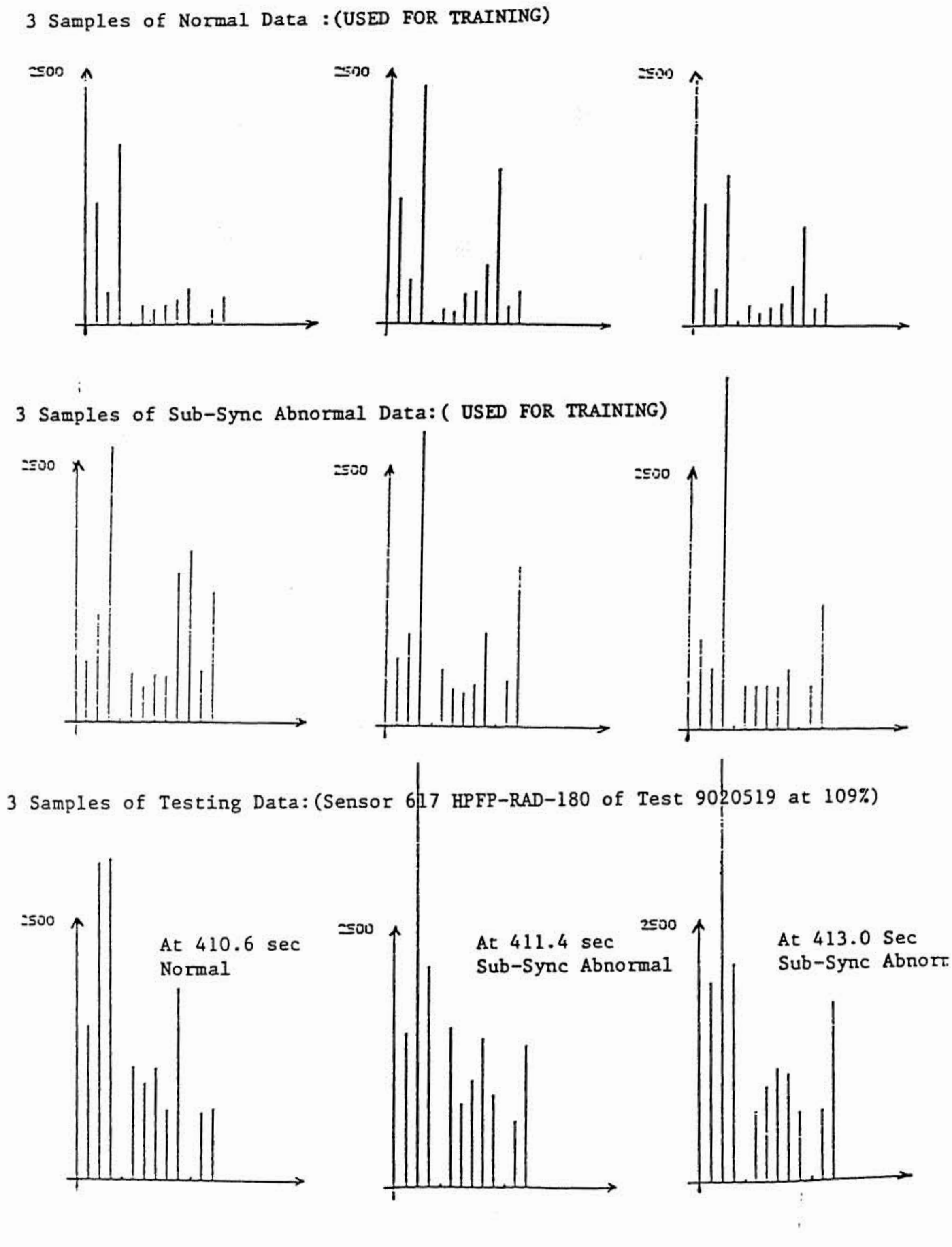

Figure 4. Samples of Normal and Sub-synchronous Abnormal Data from HPFTP Sensors of Test 902-519 at the Thrust-level 109%.

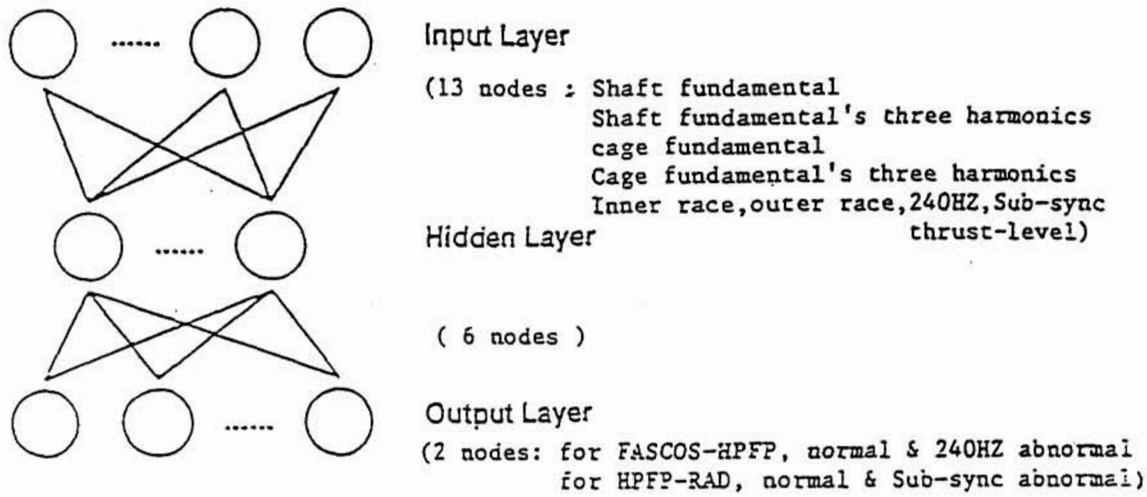

Figure 5. Three-layer Back-propagation Neural Network Architecture.